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풍력터빈 상태진단에 적용된 다양한 신경망 모델의 유효성 비교+

(Comparison of the effectiveness of various neural network models applied to wind turbine condition diagnosis)

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요 약 재생 에너지 생성에서 중요한 역할을 하는 풍력 터빈은 작동 상태를 정확하게 평가하는 것이 에너지 생산을 극대화하고 가동 중지 시간을 최소화하는 데 매우 중요하다. 이 연구는 풍력 터빈 상태 진단을 위한 다양한 신경망 모델의 비교 분석을 수행하고 센서 측정 및 과거 터빈 데이터가 포함된 데이터 세트를 사용하여 효율성을 평가하였다. 분석을 위해 2MW 이중 여자 유도 발전기 기반 풍력 터빈 시스템(모델 HQ2000)에서 수집된 감시 제어 및 데이터 수집 데이터를 활용했다. 활성화함수, 은닉층 등을 고려하여 인공신경망, 장단기기억, 순환신경망 등 다양한 신경망 모델을 구축하였다. 대칭 평균 절대 백분율 오류는 모델의 성능을 평가하는 데 사용되었다. 평가를 바탕으로 풍력 터빈 상태 진단을 위한 신경망 모델의 상대적 효율성에 관한 결론이 도출되었다. 본 연구결과는 풍력발전기의 상태진단을 위한 모델선정의 길잡이가 되며, 고도의 신경망 기반 기법을 통한 신뢰성 및 효율성 향상에 기여하고, 향후 관련연구의 방향을 제시하는데 기여한다.

핵심주제어: 상태 진단, 신경망 모델, 풍력 터빈

Abstract Wind turbines playing a critical role in renewable energy generation, accurately assessing their operational status is crucial for maximizing energy production and minimizing downtime. This study conducts a comparative analysis of different neural network models for wind turbine condition diagnosis, evaluating their effectiveness using a dataset containing sensor measurements and historical turbine data. The study utilized supervisory control and data acquisition data, collected from 2 MW doubly-fed induction generator-based wind turbine system (Model HQ2000), for the analysis. Various neural network models such as artificial neural network, long short-term memory, and recurrent neural network were built, considering factors like activation function and hidden layers. Symmetric mean absolute percentage error were used to evaluate the performance of the models. Based on the evaluation, conclusions were drawn regarding the relative effectiveness of the neural network models for wind turbine condition diagnosis. The research results guide model selection for wind turbine condition diagnosis, contributing to improved reliability and efficiency through advanced neural network-based techniques and identifying future research directions for further advancements.

Keywords: Condition diagnosis, Neural network models, Wind turbine

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1. Introduction

1.1 Significance of Diagnosing Wind Turbine Operational States in Renewable Energy

The operational states of wind turbines play a crucial role in the renewable energy industry. Wind power is a rapidly growing source of clean and sustainable energy, and wind turbines are key components in harnessing this resource. According to Olabi et al.(2023) The efficient and reliable operation of wind turbines is essential for maximizing energy production and ensuring the long-term viability of wind farms.

However, wind turbines are subjected to various operational challenges and potential faults that can impact their performance and lead to costly downtime. Therefore, accurately diagnosing the operational states of wind turbines is of paramount importance. It enables proactive maintenance, timely repairs, and optimized operation, thereby reducing downtime and enhancing the overall productivity and profitability of wind farms Zhengru Ren et al.(2021).

Effective condition diagnosis involves monitoring various parameters like vibration, temperature, power output, and other sensor measurements, enabling early fault detection and informed maintenance decisions. This improves wind turbine reliability, reduces costs, and enhances overall wind farm performance and longevity. Therefore, research and advancements in the field of wind turbine condition diagnosis are vital to the continued growth and success of the renewable energy industry.

1.2 The Role of Neural Network Models in Wind Turbine Condition Diagnosis

Neural network models have emerged as powerful tools for wind turbine condition diagnosis in recent years. These models leverage the capabilities of artificial neural networks, which are inspired by the structure and functioning of the human brain, to analyze complex patterns and make accurate predictions Alberto Pliego Marugán et al.(2018).

The flexibility of neural network models allows for customization and adaptation to different wind turbine configurations and operational contexts. The models can be tailored to specific turbines, taking into account factors such as turbine size, design, and environmental conditions. This adaptability enables the development of accurate and robust diagnosis systems for a wide range of wind turbine installations Alberto Diez-Olivan et al.(2019).

Overall, neural network models have demonstrated great potential in wind turbine condition diagnosis, offering improved accuracy, efficiency, and scalability compared to traditional diagnostic approaches. They contribute to enhancing the reliability, performance, and maintenance of wind turbines, leading to optimized energy production and reduced operational costs.

In this research, we focus on collecting and preprocessing supervisory control and data acquisition (SCADA) data from HQ2000 wind turbines for condition diagnosis. Among the various components, we select the bearing part for training the Neural Network models. We investigate the effectiveness of three models: Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks. The neural network models are trained and evaluated on the preprocessed SCADA data. Our comparative analysis reveals that LSTM demonstrates the best training performance for wind turbine condition diagnosis, achieving a low symmetric mean absolute percentage error (SMAPE) of 9.28%.

Its ability to capture long-term dependencies in time-series data contributes to more accurate and reliable predictions. While ANN and RNN models also exhibit satisfactory performance, LSTM's superior results highlight its potential as the preferred choice for wind turbine condition diagnosis.

2. Theoretical Foundation

2.1 Overview of the theoretical foundations regarding the operational states of wind turbines and related issues

The section provides an overview of the theoretical foundations and related issues surrounding wind turbine operational states, offering valuable insights for effective condition diagnosis and maintenance strategies. Wind turbines can operate in various states depending on their current mode and functionality. These states encompass normal operation, start-up, shutdown, idle, and emergency stop. Understanding each operational state is crucial for accurate diagnosis and assessment of the turbine's performance Lu Wei et al.(2020). For instance, start-up and shutdown phases involve unique challenges, such as managing power ramp-up and ramp-down sequences, while the emergency stop state requires immediate action to mitigate potential risks and ensure safety.

To evaluate wind turbine operational states, various performance parameters are considered. These parameters serve as indicators of the turbine's health, efficiency, and operational capabilities. Key performance parameters include power output, rotor speed, pitch angle, yaw misalignment, vibration levels, temperature, and electrical characteristics. Monitoring and analyzing these parameters enable the identification of deviations, anomalies, or deteriorations in the turbine's operation, thereby supporting early fault detection and diagnosis.

Wind turbines are prone to a range of potential faults that can affect their performance and longevity. Common faults include issues with the gearbox, generator, blades, bearings, electrical systems, and control systems Johan Ribrant(2006). These faults can lead to power loss, decreased efficiency, or even complete system failure. Understanding the types and characteristics of these faults is critical for effective condition diagnosis, maintenance planning, and optimizing the operational life of wind turbines.

Sensors play a vital role in capturing real-time data on various parameters within wind turbines, including wind speed, turbine vibrations, temperature differentials, strain levels, and other operating conditions. These measurements provide valuable insights into wind turbine operational states, serving as inputs for condition diagnosis algorithms and models.

Environmental factors such as wind speed, wind direction, air density, temperature, and turbulence significantly influence wind turbine performance. Changes in these factors can impact aerodynamics, load distribution, structural integrity, and power generation. Considering these environmental factors in condition diagnosis allows for a more accurate assessment of operational states and aids in understanding the turbine's interaction with its surroundings.

Various data analysis techniques are employed to extract meaningful information from the sensor measurements and diagnose wind turbine operational states. Statistical methods, signal processing techniques, and advanced machine learning algorithms, including neural networks, are utilized to analyze the collected data and identify patterns, trends, anomalies, and potential faults. These techniques enable the development of effective condition diagnosis models and algorithms, contributing to timely fault detection and improved decision-making Fausto Pedro García Márquez et al.(2012).

In conclusion, understanding the theoretical foundations regarding wind turbine operational states and related issues are essential for effective condition diagnosis, maintenance, and optimization of wind turbine systems. By comprehending the intricacies of operational states, performance parameters, potential faults, sensor measurements, environmental factors, and data analysis techniques, researchers and practitioners can develop robust strategies for diagnosing faults, optimizing operational efficiency, and ensuring the long-term reliability of wind turbines.

2.2 Overview of Neural Network models and their applications in the field of condition diagnosis for monitoring systems

Neural network models have demonstrated remarkable performance in monitoring systems' condition diagnosis, utilizing their capacity to learn and recognize patterns from high-dimensional data. Inspired by the human brain, these computational constructs adjust their weights and biases during training with labeled data, enabling them to make precise predictions for unseen data and enhance the effectiveness of condition monitoring. The power of neural networks allows for the creation of sophisticated diagnosis models, significantly improving precision and effectiveness in analyzing various systems' operations. Their ability to handle high-dimensional data and capture non-linear correlations makes them a valuable tool in condition diagnosis tasks.

Neural network models have found wide-ranging applications in condition diagnosis for various monitoring systems M. Fast et al.(2010). In the context of industrial machinery, neural networks can analyze sensor data to detect anomalies, predict faults, and diagnose the operational conditions of critical components. For example, in rotating machinery like pumps, motors, or turbines, neural networks can learn to identify patterns indicative of specific faults, such as bearing wear, imbalance, or misalignment.

In this research, the choice of comparing ANN, RNN, and LSTM networks is driven by their specific attributes and suitability for wind turbine condition diagnosis. ANN is selected due to its capacity to capture complex patterns in data. RNN, designed for sequential data, aligns well with the time-series nature of wind turbine sensor measurements. LSTM, an advanced RNN variant, excels in capturing long-term dependencies, crucial in understanding turbine operational trends. This selection maximizes the comprehensive evaluation of neural network models across a spectrum of complexities. It considers factors like capturing temporal dynamics, handling high-dimensional data, and managing non-linear correlations. By comparing these three models, we gain a holistic perspective on their performance and suitability for wind turbine condition diagnosis tasks.

The neural network models employed in this study possess distinct architectures tailored to the complexities of wind turbine condition diagnosis. These models encompass layers, nodes, and activation functions, forming the building blocks for effective learning and prediction.

- Input layer: Receives sensor data and operational parameters.
- Hidden layers: Enhance data relationship capture.
- Activation functions: Introduce non-linearity.
- Output layer: Generates predictions.

Neural network layers are connected by adaptable weights and biases, reducing prediction errors during training for accurate diagnosis. Layer arrangement, node count, and activation functions impact performance. This study underscores grasping network structure for diagnostic insights.

3. Research Methodology

3.1 Historical turbine data for condition diagnosis

To train the state diagnostic model, historical SCADA data of the wind turbine HQ2000 was collected and processed. The study used SCADA data spanning the years 2016 and 2017 of the wind turbine HQ2000 for training and validating the developed model. This dataset, comprising a comprehensive temporal span, holds immense value in capturing wind turbine operational insights. The dataset employed in this study comprises a comprehensive set of 157 variables, encompassing critical parameters such as wind speed, active power, and gearbox temperature, among others. With a time step of 10 minutes, this dataset offers a detailed, time-stamped view of wind turbine operations. Spanning from May 1, 2016, to December 31, 2017, it consists of a total of 87,840 data points corresponding with each variables, ensuring a robust and extensive foundation for in-depth analysis and modeling. The dataset's 87,840 data points are ideal for neural network analysis in wind turbine condition diagnosis. It strikes the right balance, offering statistical significance, covering diverse temporal variations, accommodating model complexity, and ensuring efficient computational processing. This dataset size aligns perfectly with the requirements for accurate and efficient neural network analysis. Through a process of data cleansing and quality control, junk and irrelevant data were removed. This refinement led to a refined dataset consisting of 58 data variables, characterized by their relevance and quality. Subsequently, the selection of pertinent features became a pivotal task. The Pearson correlation coefficient, a powerful analytical tool, was invoked to gauge the relationships between various data attributes and the gearbox bearing temperature.

SCADA data refers to the real-time measurements and operational information collected from various sensors and control systems installed on wind turbines. This data includes a wide range of parameters such as wind speed, rotor speed, power output, temperature, vibration levels, and electrical measurements. SCADA data provides valuable insights into wind turbines' performance, health, and operational states, enabling operators and maintenance personnel to monitor and control the turbines remotely, detect anomalies, and make informed decisions regarding maintenance, optimization, and overall turbine management.

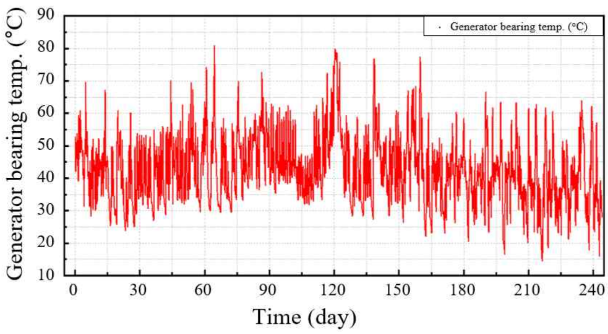


Fig. 1 Generator bearing temperature data after processing

There are a lot of error data in the raw historical data. The high sensitivity of the sensors or flaws in the data acquisition system are typically to blame for these inaccuracies. These data need to be processing before being used to train the model. Data processing is a crucial step in training neural network models for condition diagnosis. It involves tasks such as data cleaning, feature scaling, dimensionality reduction, handling imbalanced data, and handling categorical variables. These steps ensure data quality, improve model training efficiency, address data imbalance, and make the data suitable for neural network models. Data processing contributes to more accurate and reliable condition diagnosis.

To train the neural network model for wind turbine condition diagnosis, special attention was given to the bearing part as it plays a critical role in the overall performance and reliability of the turbine, making it a key component for accurate and effective condition assessment. The output data selected to build a condition diagnostic model for bearings is the generator bearing temperature. Fig. 1 shows the data after processing and is used to design a condition diagnostic model for bearing parts of the wind turbine. Operating data for generator bearing temperature varies from 14.51°C to 80.86°C. The data is divided into two categories: 15% of the data is used to verify the model's accuracy, and 85% of the data is used to train the model. The Pearson correlation coefficient is used to calculate the relationship between the data used to train the model and one another. The SCADA data feed for neural network was chosen using the Pearson correlation coefficient (PCC). The PCC is as Equation (1):

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} \tag{1}$$

Where cov is the covariance, σ_X is the standard deviation of X, and σ_Y is the standard deviation of Y.

Since the trends of state data and SCADA data are comparable, a correlation coefficient that is close to both extreme values is driven. The correlation is dispersed between −1 and +1. Fig. 2 shows the correlation coefficient between SCADA data, and the darker the blue colour is, the closer the correlation coefficient is to both extreme values. The correlation coefficient was calculated, and SCADA data

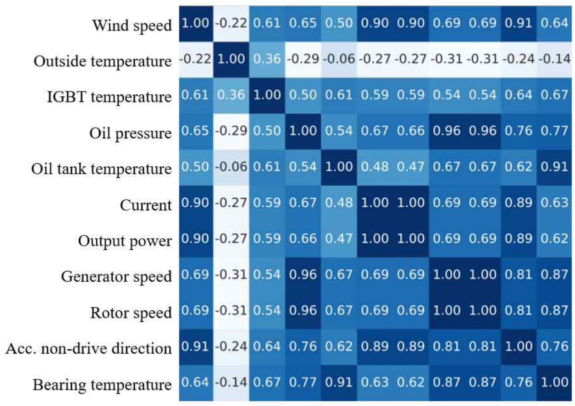


Fig. 2 Correlation coefficient graph between SCADA data

Table 1 Pearson correlation coefficient for gearbox bearing temperature

Input data	PCC
Oil inlet pressure	0.767
Gearbox oil tank temp.	0.914
Generator speed	0.866
Acc non drive direction	0.757

close to −1 of +1 were chosen. In order to increase the precision of machine learning, the scaled SCADA data were chosen using the correlation coefficient.

Table 1 shows high PCC data for generator bearing temperatures. These data will be used as input data for the neural network.

3.2 Neural network models employed for condition diagnosis

In the field of condition diagnosis, various types of neural network models have been employed to analyze and predict the operational states of wind turbines. This section focuses on three commonly used neural network models: ANN, RNN, and LSTM networks.

ANN are key for wind turbine condition diagnosis. They learn complex data relationships, adjusting weights during training for accurate predictions John J. Hopfield(1988). RNN excel in time-series tasks, capturing dependencies. However, traditional RNN face gradient vanishing. LSTM networks, an advanced RNN type, overcome this. LSTM models process sequential sensor data, identify patterns, and detect anomalies, ensuring precise diagnostics Roeland De Geest et al.(2018).

Modeling wind turbines using neural networks involves a systematic approach that utilizes computational capabilities to understand and predict operations. Key steps include:

- Data Collection and Preprocessing: Gather comprehensive sensor data and refine it through preprocessing.
- Data Segmentation: Divide data into training, validation, and testing subsets.
- Architecture Design: Configure network layers, nodes, and activation functions.
- Feature Selection: Choose relevant features influencing turbine states.
- Model Training: Train the network using data and optimization algorithms.
- Hyperparameter Refinement: Fine-tune parameters for better generalization.
- Performance Evaluation: Assess model capabilities using testing data.
- Enhancement Iterations: Explore additional layers or optimization techniques.
- Prediction and Insight: Utilize trained models for real-time predictions.
- Continual Enhancement: Retrain models with accumulating data for ongoing effectiveness.

The selection of the appropriate neural network model depends on the specific characteristics of the wind turbine condition diagnosis task and the available data. In this research, we use SMAPE as the evaluation metric to assess the training performance of different models. The models are trained on labeled data and evaluated on unseen data to assess their predictive capabilities and generalization ability.

4. Results and Discussion

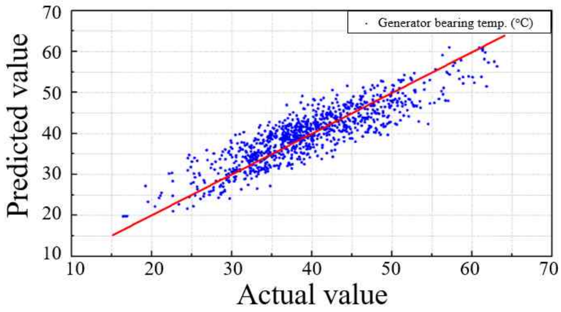
4.1 Comparative Results of Neural Network Models

After training and optimizing the models with different design factors such as activation function, learning rate, number of hidden layers, training performance of each model is shown in Fig. 3 and Table 2. The best fit results line in a graph signifies a balanced relationship between the predicted and actual values. When data points on the scatter plot lie close to or approximately along the best fit line, it indicates that the values of the predicted and actual tend to increase or decrease together. According to the Fig.3 and Table 2, the ANN model achieved a SMAPE of 10.70%, indicating its ability to capture the operational condition of the generator bearing with reasonable accuracy. The RNN model, on the other hand, yielded a slightly higher SMAPE value of 11.25%, suggesting a slightly reduced performance compared to ANN. However, it is worth noting that RNN models still demonstrated a satisfactory level of predictive accuracy. Notably, the LSTM model exhibited the best performance among the three models, with a significantly lower SMAPE of 9.28%. This result indicates that LSTM models effectively captured the complex patterns and dependencies in the wind turbine operational condition, leading to more accurate condition diagnosis.

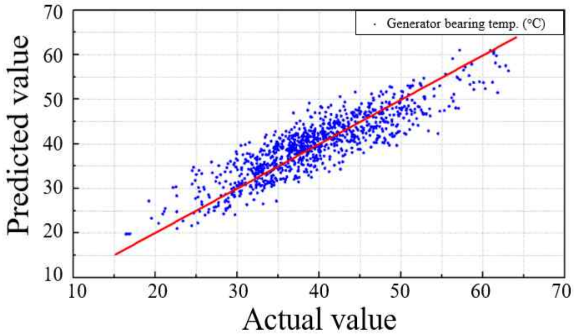
Based on the comparative analysis, LSTM models exhibit a slight advantage over ANN and traditional RNN models in gearbox bearing condition diagnosis. Their ability to capture long-term dependencies and retain important information over time contributes to improved predictive accuracy. However, the specific performance of neural network models may vary on factors such as the dataset, model architecture, hyperparameter tuning, and the characteristics of the wind turbine system under consideration.

We should consider these comparative results and evaluate the trade-offs between model complexity and predictive accuracy when selecting the appropriate neural network model for wind turbine condition diagnosis. Further research can focus on optimizing the architecture and hyperparameters of LSTM models to maximize their performance and address specific challenges encountered in wind turbine condition diagnosis tasks.

In summary, To recap, the comparative analysis suggests a slight edge for LSTM models over ANN and traditional RNN models in gearbox bearing condition diagnosis. Nevertheless, a comprehensive understanding of the variables influencing model performance demands further investigation and experimentation. In the future, the trajectory of wind turbine condition diagnosis involves exploring a wider array of newer and improved neural network techniques. These endeavors are poised to augment the arsenal of diagnostic tools, aligning them with advancements in technology and the evolving objectives of wind turbine condition diagnosis.



(a)



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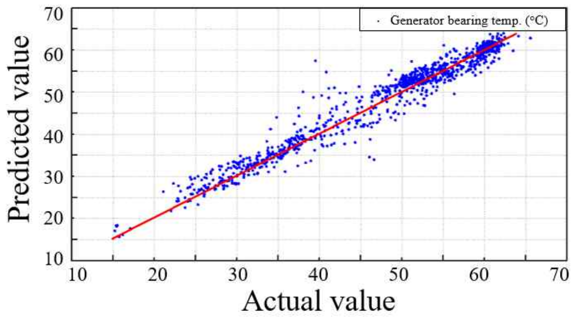

(c)

Fig. 3 Training performance of the neural network: a) ANN model, b) RNN model, c) LSTM model

Table 2 Training performance of different algorithms for generator bearing

Neural network model	SMAPE(%)
ANN	10.70
RNN	11.25
LSTM	9.28

4.2 Advantages and Limitations of Neural Network Models

Neural network models, including ANN, RNN, and LSTM networks, have demonstrated their effectiveness in wind turbine condition diagnosis. This section highlights the advantages and limitations of these models based on the comparative results presented earlier.

A. Advantages of Neural Network Models

ANN: Artificial Neural Networks offer potent pattern recognition, capturing intricate data relationships. Versatile across data types, including wind turbine sensor data, they excel in non-linear relationship capture and accurate predictions.

RNN: Recurrent Neural Networks specialize in sequential data, apt for time-series analysis in turbine condition diagnosis. Their temporal dependency capture yields precise predictions. Varying time-series lengths enable historical sensor data analysis.

LSTM: Long Short-Term Memory networks enhance traditional RNNs with memory cells, adept at long-term dependency capture crucial for wind turbine diagnosis. Retaining vital data over time refines predictions, particularly for nuanced patterns and complex fault identification.

B. Limitations of Neural Network Models

ANN: Artificial Neural Networks struggle with capturing lengthy dependencies in time-series data due to their feedforward architecture. This limitation impacts predictive accuracy in turbine diagnosis tasks reliant on sequence information. Optimal performance may demand abundant training data and intricate structures.

RNN: Traditional Recurrent Neural Networks face the "vanishing gradient" hurdle, hindering accurate long-term dependency capture. This issue affects wind turbine diagnosis, especially with intricate temporal patterns or extended variations. Training RNN models can be computationally intense.

LSTM: While LSTM networks overcome RNN limitations, they're complex and computationally demanding. Specialized memory cells and additional parameters amplify overhead. Consequently, training and optimizing LSTMs demand more time and resources compared to simpler models.

5. Conclusion and Future Developments

In this paper, we explored the effectiveness of neural network models, including ANN, RNN, and LSTM networks, in wind turbine condition diagnosis. Through a comparative analysis, we identified the advantages, limitations, and comparative performance of these models.

Based on the results, LSTM models demonstrated slightly better predictive accuracy in gearbox bearing condition diagnosis compared to ANN and traditional RNN models. Their ability to capture long-term dependencies and retain important information over time contributed to improved diagnostic accuracy. However, it is important to consider the specific characteristics of the wind turbine system and the dataset when selecting the most appropriate model.

Currently, LSTM stands out as the most effective among the three networks. However, our future plans involve exploring and implementing innovative techniques to further enhance the training of the condition diagnosis model. This proactive approach aims to continuously improve the accuracy and reliability of wind turbine condition assessment, ensuring optimal performance in the evolving landscape of renewable energy technology. Additionally, integrating other data sources, such as meteorological data and historical maintenance records, can improve diagnosis accuracy and reliability. Exploring ensemble methods that combine multiple neural network models can lead to more robust and accurate diagnostic results. Moreover, enhancing the explainability and interpretability of neural network models through attention mechanisms or model-agnostic interpretability methods can foster better understanding and trust in the diagnosis outcomes. These advancements hold the potential to revolutionize wind turbine condition diagnosis, resulting in more reliable and efficient operations in the renewable energy industry.

In conclusion, neural network models, including ANN, RNN, and LSTM, have shown promise in wind turbine condition diagnosis. LSTM models demonstrated slightly better predictive accuracy due to their ability to capture long-term dependencies. However, the selection of the most appropriate model should consider the specific characteristics of the wind turbine system and the dataset. Future developments should focus on model optimization, integration of additional data sources, ensemble methods, and improving the explainability and interpretability of the models. These advancements will contribute to more accurate, reliable, and actionable wind turbine condition diagnosis, enhancing the performance and longevity of wind energy systems.

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